Evolution of Elasticity of Demand for Coal in China and the United States

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Abstract

We present a replication of the main analysis in Burke and Liao (2015), which employs an OLS design and aggregated coal price and consumption data to estimate the elasticity of demand for coal in China from 1998 to 2012. The study documents increasingly elastic demand during the time period which they attribute to the removal of government price controls. We extend this analysis to the United States coal market from 2002 to 2021. We use contracts between coal mines and power plants and an IV estimation strategy to find that demand has grown more inelastic in the US over the last two decades. Our results are consistent with fundamental differences that exist between China and the US with respect to institutional features and broader energy use trends.

1 Introduction

Coal is the largest source of electricity generation globally (Information Energy Agency). It is also the single largest source of carbon dioxide emissions, and its use has been linked to a laundry list of negative health and environmental outcomes (Hendryx et al. (2020)). Understanding the market for coal is of particular interest in policy discussions regarding incentive structures which best facilitate a transition to cleaner, greener sources of energy.

Fundamental to an economic analysis of any market is an accurate estimation of the elasticity of demand. So, what is the price elasticity of demand for coal? How has price

*For data, code, and replication materials, see https://github.com/gelkouh/econ-21110-winter-2023.

elasticity of demand for coal changed over time? Are trends in the elasticity of demand for coal consistent across geographies and market structures? Economists and policymakers alike in search of answers to these questions were previously left with gaps in the literature as dark and desolate as an abandoned mine shaft. With this paper, we say: "Let there be light!"[1]

We first replicate the main results of Burke and Liao (2015), which focuses exclusively on the question: "Is the price elasticity of demand for coal in China increasing?" In the time period from 1998 to 2012, this paper finds that the price elasticity of demand for coal in China became more elastic. The authors attribute this trend primarily to China's rolling back price controls that previously maintained artificially inelastic demand for coal. Data on prices and quantities of coal demanded are aggregated to the year and province level. Elasticities are estimated via OLS with a selection on observables strategy. We are able to replicate the main findings of this study. While there are some minor discrepancies in the estimates we arrive at, these seem to be a consequence of a small amount of data used in the original paper that the authors did not include in their replication data file.

We extend the analysis of Burke and Liao (2015) by exploring trends in the price elasticity of demand for coal in the US. We implement solutions to several key issues with the identification strategy of the original paper with our extension. First, we avoid any potential aggregation bias by using the most granular data available: individual contracts with price and quantity data between coal mines and power plants. Second, while we do present results using the Burke and Liao (2015) empirical design for comparison, we introduce a coal mine's coal seam height as a novel instrument for coal price to overcome endogeneity and omitted variable bias in the OLS specification. We find that the price elasticity of demand for coal has generally become more inelastic in the US over the time period of 2002-2021.

Section 2 presents our replication of the analysis in Burke and Liao (2015); section 3 presents our extension of the analysis to the US coal market; and section 4 concludes. Note that all tables and figures referenced are in section 6, the appendix.

1. Lest the critical reader question our humility, we regretfully admit there remain several puzzling aspects of our results. These are explored in the coming sections.

2 Replication

2.1 Data

The replication file provided by the authors contains the data necessary to approximately reproduce the main results of the paper.[2] The authors use yearly province-level panel data from 1998 to 2012. The full panel covers 30 provincial-level divisions in mainland China: 22 formal provinces, 4 municipalities (Beijing, Tianjin, Shanghai, and Chongqing), and 4 autonomous regions (Inner Mongolia, Guangxi, Ningxia, and Xinjiang). We provide a summary of the relevant variables in the data in Table 1, which summarizes the variables on coal consumption, price, time, and real GDP (in 2012 rmb) and corresponds to Table 1 in the original paper. The primary sources for this data are the CEIC, China's National Bureau of Statistics, the China Electricity Council, and the National Development and Reform Commission.

The replication data file is missing some values toward the end of the sample period. This is illustrated in Figure 1, which corresponds to Figure 4 in the original paper. In particular, note that in Figure 1, Panel A the original paper's data reflects deflation in the price of coal toward the end of the sample period; in Figure 1, Panel B, we can see that this trend does not appear in the replication data file. From this figure alone, it is not clear before conducting the full analysis how this missing data biases the final elasticity estimates. But we will ultimately see that these missing data do not substantially affect our replication effort, and we were able to reproduce the main results of Burke and Liao (2015) fairly accurately.

2.2 Empirical strategy

The main specification of Burke and Liao (2015) is a basic log-log demand model:

$$\ln(C_{pt}) = \beta_1 \ln(P_{pt}) + \beta_2 \ln(Y_{pt}) + \beta_3 t + \delta_p + \epsilon_{pt}, \tag{1}$$

where $t \in \{0, ..., T\}$ is a linear time trend (with units in years), p is the province in China, C_{pt} is primary coal consumption, P_{pt} is an output price index, Y_{pt} is real GDP, and δ_p is a province fixed effect. The authors suggest that equation (1) exploits within-province

2. The replication data file is publically available via the Harvard Dataverse at https://doi.org/10.7910/DVN/FFKURT. The authors do not provide code to replicate their analysis. Our code is in our replication package hosted on GitHub and linked in the footnote on the first page of this document.

temporal variation and that the estimate of β_1, $\hat{\beta}_1$, should be interpreted as a short-run elasticity of demand.

To gain insight into the central question of the paper regarding changes in the price elasticity of demand for coal over time, a second specification that interacts the linear time trend and output price index is used:

$$\ln(C_{pt}) = \beta_1 \ln(P_{pt}) + \beta_2 \ln(Y_{pt}) + \beta_3 t + \beta_4 (t \times \ln(P_{pt})) + \delta_p + \epsilon_{pt}. \tag{2}$$

Finally, to capture the fact that adjustments to changes in coal prices take time and that coal contracts often extend over more than one year, the authors employ an additional specification that incorporates lagged price as a covariate:

$$\ln(C_{pt}) = \beta_1 \ln(P_{pt}) + \beta_2 \ln(Y_{pt}) + \beta_3 t + \beta_4 (t \times \ln(P_{pt})) + \beta_5 \ln(P_{pt-2}) + \beta_6 \ln(t \times P_{pt-2}) + \delta_p + \epsilon_{pt}. \tag{3}$$

The primary drawback of the approach Burke and Liao (2015) use is the restrictive functional form assumption implied by the use of a linear time trend rather than time fixed effects. It is especially troubling that a linear time trend is used given the institutional setting of the paper. At the beginning of the sample period, price controls were relaxed. At this point, we might expect a larger increase in price elasticity than the one that occurs during the final years of the sample. Perhaps using time dummies would have been a better strategy; in our extension we use specifications with time dummies to overcome these potential drawbacks that a linear time trend imposes. It should be noted, however, that the trend in Figure 1, Panel B evinces a fairly linear relationship between time and coal price index following the easing of price controls. If a similar trend holds for the price elasticity relationship, a linear time trend may be an appropriate feature of the specification.

2.3 Empirical results

Table 3 provides estimates of equations (1), (2), (3) for the full sample as well as an "early" and "late" period (defined as 1998-2007 and 2008-2012, respectively). Details on the samples corresponding to each column are provided in the note attached to Table 3 in the appendix.

Standard errors are clustered at the province level. This table corresponds to Table 2 in the original paper and presents the main findings of Burke and Liao (2015). The missing data do not appear to have biased our estimates in a consistent direction. For example, column (1) presents an estimate that is lower than the original paper's, whereas column (4) presents an estimate that is higher than the original paper's. All discrepancies, despite missing data, fall within the range of the standard errors.

Consistent with Burke and Liao (2015), our replication suggests increasingly elastic demand for coal over the sample period in China. This is demonstrated by the "more negative" coefficients on the coal price index in the late vs. early periods (compare columns (2) to (3) and (7) to (8), respectively) and the negative and statistically significant sign of estimated coefficient on the time trend and coal price index interaction term in columns (4) and (9). From the estimates in Table 3, we can calculate a point estimate of the elasticity of demand for coal in China at various points in the sample period. A graphical depiction of the change in the estimated demand elasticity over time in China (using the estimates in columns (7) and (8) in Table 3) is presented in Figure 3, Panel A.

3 Extension

3.1 Data

To study the elasticity of demand for coal in the US, we use a sample of 135,315 supply contracts for bituminous coal between coal mines and power plants. These were accessed via S&P Capital IQ. Bituminous coal is the most commonly mined type of coal in the US. The contracts have delivery dates for coal from 2002 to 2021. Each contract states a quantity of coal and the price paid per ton. To adjust the contract prices for inflation, we use the monthly coal mining Producer Price Index from FRED. The contracts are supplemented with the contracting power plant's state annual GDP from the BEA.[3]

We employ an instrumental variables design, which uses a contracting mine's coal seam height as an instrument for contracted price per ton. Annual mine coal seam data is from S&P Capital IQ. Coal seam height is a fairly direct measure of the quantity of mineable coal a particular mine has available to sell to a power plant. Further justification for its use and validity as an instrument is given in the section outlining our empirical strategy below. Note that our coal seam height sample only includes underground mines, so any resulting elasticity estimates are just of the elasticity of demand for coal from underground bituminous

3. A link to a Google Drive folder that contains the data that constitute our sample is available at our aforementioned GitHub replication package. This is necessary to replicate our results as data on S&P Capital IQ is not easily accessible elsewhere.

mines. The fact that most bituminous coal is mined underground anyway diminishes the threat this poses to the external validity of our estimates.

Note that, even among underground mines, not all contracting mines in our sample are present in the coal seam height data. Table 2 provides summary statistics. In addition to substantial variation in contracted quantities and prices, we can see that we are only able to link about 32,290 of the contracts with the coal seam height data (about 24 percent of contracts in our sample).

We restrict our sample to long-term supply contracts between coal mines and coal-powered power plants. These contracts constitute the majority of the sample we have access to and do not exhibit the same short-term volatility in prices that, e.g., spot market contracts do. Hence, long-term supply contracts are better for estimating changes in elasticities over long periods of time, which is the goal of this project.

3.2 Empirical strategy

We first estimate the following OLS specification, which allows for a direct — although, as we explain below, potentially biased — comparison of our US sample to the China coal market, as it is analogous to the one that Burke and Liao (2015) introduce:

$$\ln(Quantity_{it}) = \beta_1 \ln(Price_{it}) + \gamma_t \left(t \times \ln(Price_{it})\right) + \tilde{\gamma}_t t + \beta_2 \ln(Y_{it}) + \theta_i + \epsilon_{it}, \qquad (4)$$

where $t \in \{0, ..., T\}$ is a linear time trend, i is the individual contract, $Quantity_{it}$ is the contracted quantity of coal in tons, $Price_{it}$ is the contracted price per ton of coal, Y_{it} is real GDP in the contracting power plant's state, and θ_i is a contracting power plant fixed effect.

Demand estimation is generally subject to a simultaneity problem, that is, we are unable to determine the elasticity of demand by naively using the observed equilibrium prices and quantities demanded. As a result, we would expect the OLS estimate for the elasticity of demand to be biased and inconsistent.

3.2.1 Identification

To resolve this endogeneity problem, it is typical to use some kind of exogenous cost shock or supply shifter as an instrument for price, allowing us to isolate the effect of price on quantity demanded and trace out the demand curve.

Since the paper we replicated did not use IV estimation, potentially due to a lack of a strong instrument, there are likely concerns related to identification of the parameter of interest, here elasticity of demand. To improve upon the methodology in Burke and Liao (2015), we find and use a novel instrument to estimate the elasticity of demand for coal in the US.

Since we are using an instrumental variable, we should naturally consider the two main assumptions necessary for a consistent IV estimator: (1) relevance $Cov(Z, X) \neq 0$ and (2) exogeneity i.e. $Cov(Z, U) = 0$, where Z is an instrument for X and U is the error term of the OLS structural specification. We provide evidence for relevance in Figure 2 of the appendix and find that our instrument is extremely strong for the specifications using a linear time trend based on the large F-statistic. For the specifications using time dummies, we may have an issue of weak instruments involving some of the the time dummy interaction terms. We will discuss this at greater length in the Empirical results section below. While we are unable to prove exogeneity, the argument for the exogeneity of the coal seam height in this context is strong. The coal seam height is a geological feature of coal mines that should not affect the quantity of coal demanded from a mine except via the price that a mine is willing to offer coal to a power plant. Coal seam height is not necessarily constant over time; for example, an increase in the coal seam height (via a discovery, mine expansion, etc.) would be akin to an exogeneous supply shock shifting the coal mine's supply curve to the right.

3.2.2 Specifications

For our main specification, since we want to observe the potential time trend in the elasticity, we additionally include a linear time trend term in our specification similar to that of the original paper. We further expand upon this specification for both the OLS and IV specifications by adding time fixed effects and interactions via time dummies. This allows us to address potential issues with heterogeneity in time effects and relax functional form assumptions imposed by a linear time trend. The specifications for our IV strategy are presented below, where equation 5 presents the structural equation and 6a and 6b present the system of first-stage equations:

$$\ln(Quantity_{it}) = \beta_1 \ln(Price_{it}) + \gamma_t \left(t \times \ln(Price_{it})\right) + \tilde{\gamma}_t t + X'_{it}\beta_2 + \theta_i + \epsilon_{it} \tag{5}$$

$$\ln(Price_{it}) = \pi_{01} SeamHeight_{it} + \alpha_{0t} \left(t \times SeamHeight_{it}\right) + \tilde{\alpha}_{0t} t + X'_{it}\pi_{02} + \theta_i + \nu_{0it} \tag{6a}$$

$$t \times ln(Price_{it}) = \pi_{11} SeamHeight_{it} + \alpha_{1t} \left(t \times SeamHeight_{it}\right) + \tilde{\alpha}_{1t} t + X_{it}' \pi_{12} + \theta_i + \nu_{1it} \quad (6b)$$

We use notation such that for some variable W_{it}, this variable represents W at time t for $t \in \{0, ..., T\}$ and i is the ith contract. Quantity and Price are in tons and SeamHeight is the coal seam height for the contracting mine in inches, with X representing a vector of covariates including real GDP. A contracting power plant fixed effect is represented by θ_i.

The specifications that include time dummies are defined similarly but have a system of first-stage equations (with form indicated by (8a), (8b)) proportional to the number of time dummies:

$$\ln(Quantity_{it}) = \beta_1 \ln(Price_{it}) + \sum_{t=0}^{T} \gamma_t \left(\tau_t \times \ln(Price_{it})\right) + \sum_{t=0}^{T} \tilde{\gamma}_t \tau_t + X_{it}' \beta_2 + \epsilon_{it} \quad (7)$$

$$\tau_1 \times \ln(Price_{i1}) = \pi_{11} SeamHeight_{it} + \sum_{t=0}^{T} \alpha_{1t} \left(\tau_t \times SeamHeight_{it}\right) + \sum_{t=0}^{T} \tilde{\alpha}_{1t} \tau_t + X_{it}' \pi_{12} + \nu_{1it} \quad (8a)$$

$$\vdots$$

$$\tau_T \times \ln(Price_{iT}) = \pi_{T1} SeamHeight_{it} + \sum_{t=0}^{T} \alpha_{Tt} \left(\tau_t \times SeamHeight_{it}\right) + \sum_{t=0}^{T} \tilde{\alpha}_{Tt} \tau_t + X_{it}' \pi_{T2} + \nu_{Tit}, \quad (8b)$$

where τ_t is the time fixed effect for time $t \in \{1, ..., T\}$ (the base case of $t = 0$ is excluded in the estimations).

3.3 Empirical results

We present the results in Tables 4, 5, and 6, with time entering linearly in Table 4 and as a set of time dummies in Tables 5 and 6. The corresponding graph for the binned estimates in Table 6 can be found in Figure 3, Panel B. We also present the first stage F-stats for the specification involving a linear time trend in Figure 2 and find that the Wu-Hausman test strongly rejects exogeneity in our setting.

First comparing the linear time and dummies specifications, we find that the point estimates are fairly similar when using the full sample across both specifications, with the point estimate being around -8.1 to -8.4. Since this is demand elasticity, we can interpret the estimate as a 1 percent increase in price causing an approximately 8 percent decrease in quantity of coal demanded *ceteris paribus*. However, while our most complete specification provides results in line with our expectations, we see that variations in specifications, specifically comparing the IV results of the early and later periods, we see that the demand elasticity is positive and decreasing from the early period to the later period. We can potentially attribute this likely biased result to a combination of misspecified functional form due to time entering linearly as well as serial correlation. The coefficients of OLS and IV estimates often have different signs, with the IV strategy suggesting a more inelastic demand developing over time while the OLS strategy suggesting that little to no change in demand elasticity occurred over the sample period. This may be due to selection bias (recall that the IV estimates use a subset of underground mines), but it is not obvious why these demand from these coal mines would would be so different that we would get these divergent results.

Whether the OLS or IV strategy gives a less biased result with weak instruments depends on the asymptotic bias of the two estimators and, in particular, on the relative sizes of $\rho_{X,U}$ vs. $\frac{\rho_{Z,U}}{\rho_{Z,X}}$, where Z is an instrument for X and U is the error term of the OLS structural specification. If $\rho_{Z,U}$ is truly exogenous, then the IV strategy is unbiased regardless of the strength of the first stage if OLS is biased at all. But it is unlikely our instrument is entirely exogenous (i.e., $\rho_{Z,X}$ is small), which means we likely have a biased IV estimator.

Comparing Tables 4 and 5, we see that the point estimate when binning the time effects and interactions is slightly smaller in magnitude while also remaining statistically significant. This could potentially be due to a weak instruments problem which may arise due to the addition of interaction terms with the endogenous variable. Indeed, for many of the first-stage regressions, the t-values on the time dummy and coal seam height interaction instruments are not statistically significant.[4] Weak instruments can lead to an estimate that is consistent and biased. These weak first stages would explain why the IV estimates appear inflated compared to the OLS estimates in tables 5 and 6.

Generally in the case of weak instruments TSLS is biased. In particular, here we are essentially creating a weak instruments problem in a panel data setting via the introduction of interactions between our endogenous regressor and time dummies. In the just-identified case i.e. without interactions, we show that the instrument is strong in Table 6. However,

4. We do not include the first stage regressions for all our IV specifications in this writeup because doing so would add over 30 pages to the document. The t-values on the first-stage instruments, as well as all relevant Wu-Hausman tests, can be examined individually at https://github.com/gelkouh/econ-21110-winter-2023/blob/main/code/extension_regression_analysis.log.

interactions between the endogenous and time dummies results in the need to include interactions between the instrument and time dummies in the first stage. Since some of these instruments may be weak, we run into an interesting problem of potentially many weak instruments. However, this problem goes beyond the primary intention of this paper and extension. As such, further discussion is relegated to the conclusion.

4 Conclusion

In our replication and extension, we sought to estimate the elasticity of demand for coal in China and the US and see how the elasticity evolved over time, keeping in mind institutional differences between the two markets as well as larger trends in coal markets. After successfully replicating the main results of the paper, we find that our hypothesis is correct. In particular, we see that demand for coal becomes more elastic in the China market, likely due to loosening price controls, while demand for coal becomes more inelastic in the US. Depending on the specification, we also have evidence that demand elasticity does not change statistically significantly during the sample period we examine. We attribute this to (1) the lack of structural change to the coal market in the US and (2) a general trend away from coal use in power generation. Our hypothesis for the latter is that power plants who continue to use coal are likely those who for some structural reason cannot switch to other sources of power. As a result, since they are dependent on coal, the overall demand for coal for these remaining plants is more inelastic, since those who were more elastic likely had exited this market. Indeed, many coal-fired power plants that have been able to have been re-outfitted in recent years to use more sustainable sources of fuel (Energy Information Administration).

In our estimation of coal demand elasticity in the US, we implement a strong novel instrument as an exogenous supply shifter. However, due to the nature of our setting and the question we sought to answer, we incorporated additional interactions between the endogenous regressor, here log price, and our time fixed effects. As a result, it is likely that some of the interactions are weak instruments as seen in some of the specifications in the log file (omitted due to length constraints). Since TSLS is biased when facing many weak instruments, it is likely that our estimates in Tables 4, 5, and 6 are biased.

While we did not discuss ways to address this issue in this class, a brief survey of the literature reveals a wealth of alternative estimators to TSLS which are robust to the many weak instruments setting. Some examples include the Jackknife IV estimator (JIVE) as described in Angrist, Imbens, and Krueger (1999) as well as its regularized variant RJIVE from Kozbur and Hansen (2014). More complex estimators which have been introduced in recent years include Post-Lasso IV from Belloni et al (2015) as well as Double Machine Learning from Chernozhukov et al (2018). While these estimators are consistent and exhibit higher finite sample efficiency under many weak instruments than TSLS, they may not be suitable to our panel data setting due to serial correlation where fixed effects may not be a suitable solution due to the nature of the construction of these estimators. Therefore, we may appeal to Chao, Swanson, and Woutersen (2023), who propose a new Jackknife IV estimator suitable to a panel data setting which in theory could be an optimal estimator in our setting, although the previously discussed estimators may still be useful in the case of functional form restrictions and sparse vs dense models.

5 References

Angrist, J. D., G. W. Imbens, and A. B. Krueger. "Jackknife Instrumental Variables Estimation." Journal of Applied Econometrics 14, no. 1 (1999): 57–67. http://www.jstor.org/stable/223249.

Belloni, Alexandre, Daniel Chen, Victor Chernozhukov, and Christian Hansen. "Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain", 2010. https://doi.org/10.48550/ARXIV.1010.4345.

Burke, Paul J., and Hua Liao. "Is the price elasticity of demand for coal in China increasing?." China Economic Review 36 (2015): 309-322. https://doi.org/10.1016/j.chieco.2015.10.004.

Chernozhukov, Victor, Denis Chetverikov, Mert Demirer, Esther Duflo, Christian Hansen, Whitney Newey, and James Robins. "Double/Debiased Machine Learning for Treatment and Causal Parameters". arXiv, 2016. https://doi.org/10.48550/ARXIV.1608.00060.

Chao, John C., Norman R. Swanson, Tiemen Woutersen, Jackknife estimation of a cluster-sample IV regression model with many weak instruments, Journal of Econometrics, 2023. https://doi.org/10.1016/j.jeconom.2022.12.011

Energy Information Administration. "More than 100 coal-fired plants have been replaced or converted to natural gas since 2011." Energy Information Administration (August 5, 2020).

https://www.eia.gov/todayinenergy/detail.php?id=44636.

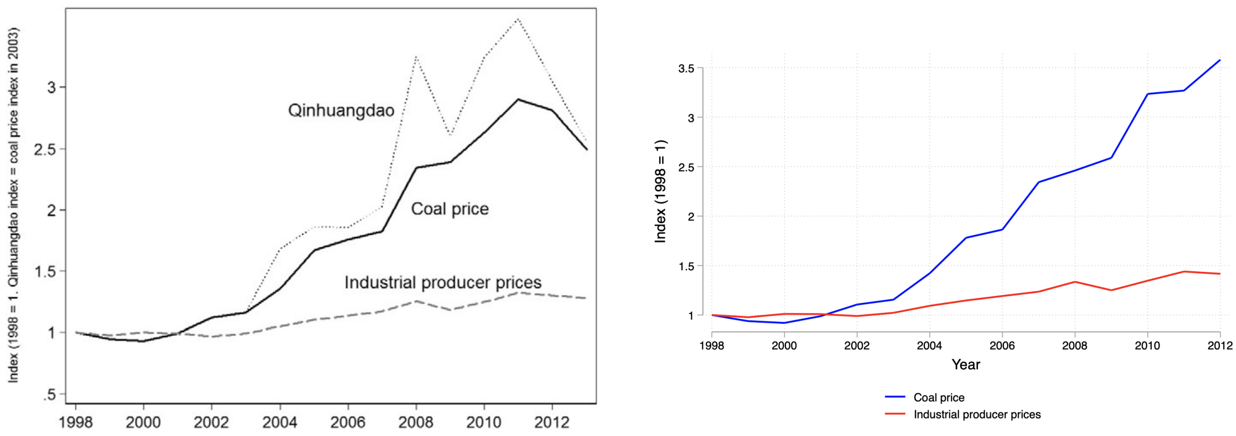
Hansen, Christian, and Damian Kozbur. "Instrumental Variables Estimation with Many Weak Instruments Using Regularized JIVE." Journal of Econometrics 182, no. 2, (2014): 290-308: https://econpapers.repec.org/article/eeeeconom/v_3a182_3ay_3a2014_3ai_3a2_3ap_3a290-308.htm.

Hendryx, Michael, Keith J. Zullig, and Juhua Luo. "Impacts of coal use on health." Annual review of public health 41 (2020): 397-415. https://www.annualreviews.org/doi/10.1146/annurev-publhealth-040119-094104

International Energy Agency. "Coal." International Energy Agency. https://www.iea.org/fuels-and-technologies/coal

6 Appendix

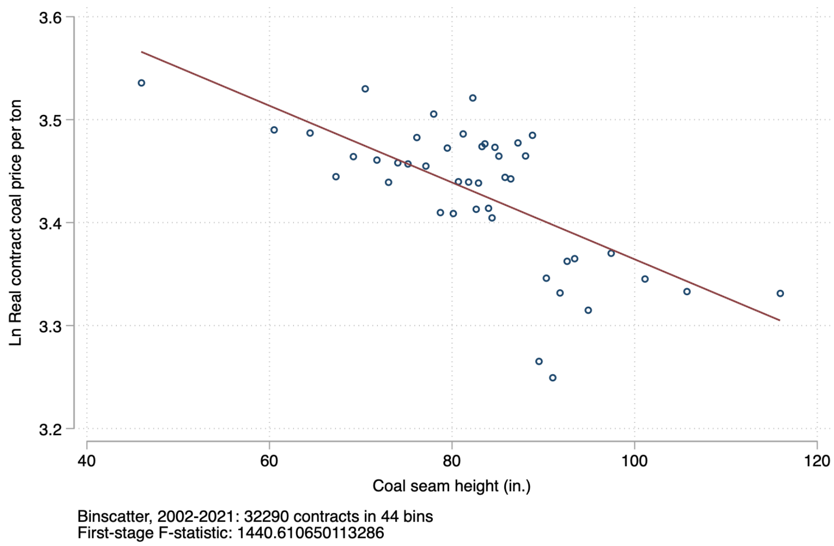
6.1 Figures



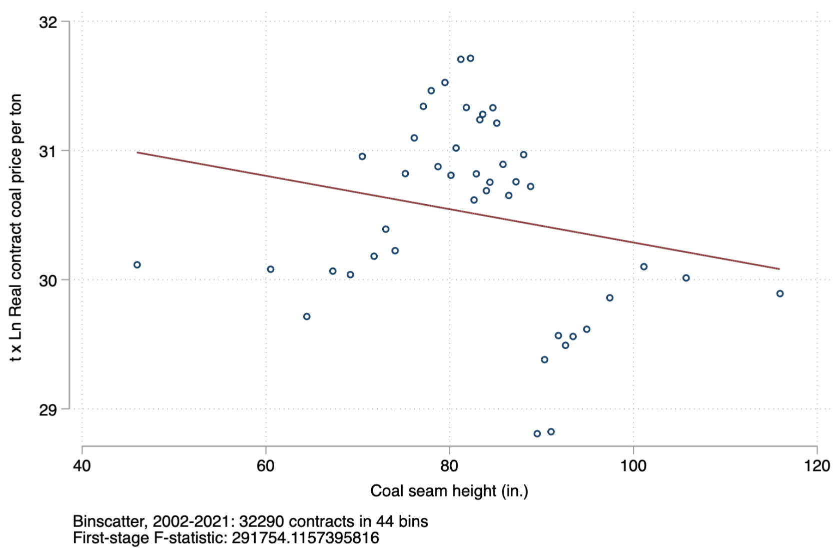
(a) Burke and Liao (2015)

(b) Replication

Figure 1: China coal price and PPI time series

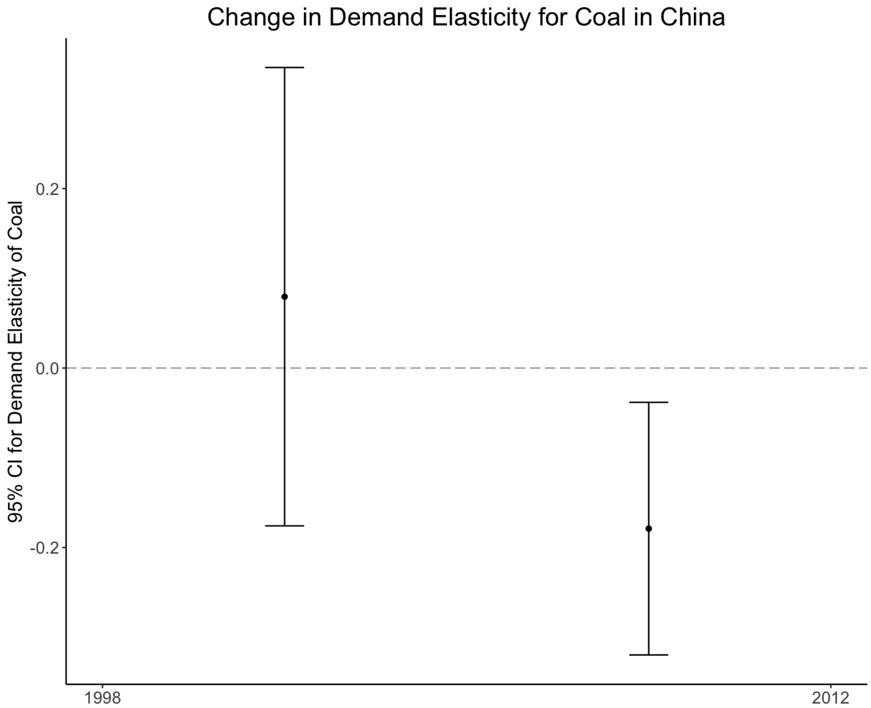


(a)

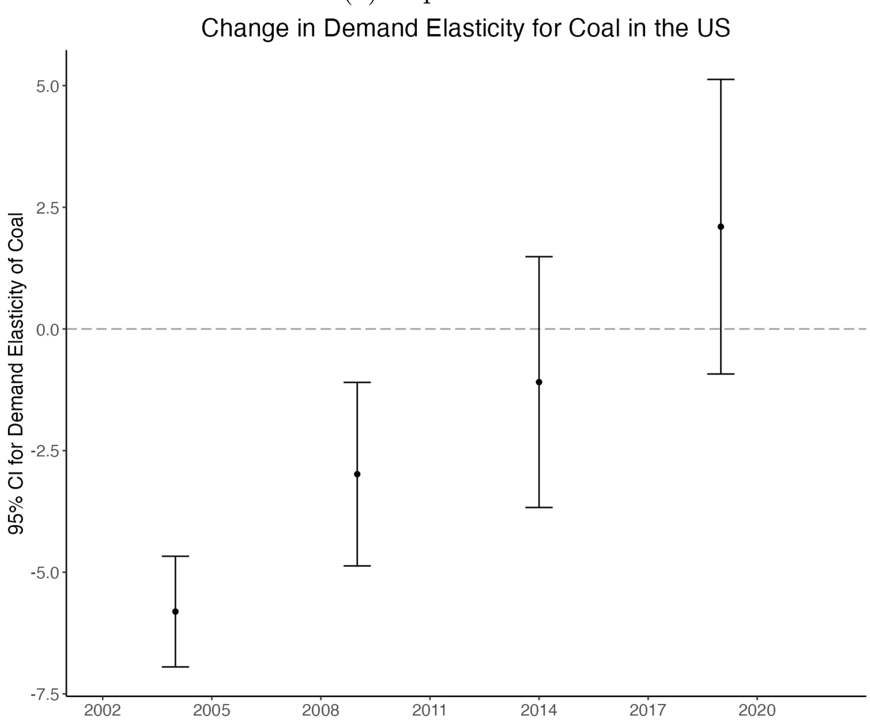


(b)

Figure 2: Coal seam height instrument first stage binscatters, linear time trend



(a) Replication



(b) Extension

Figure 3: Elasticity estimates over time

6.2 Tables

	mean	sd	min	max
Ln Coal consumption	4.106663	.9305527	.5247285	5.997397
Ln Real coal price index	4.098127	.4318536	2.793868	4.774778
Time trend	7	4.325147	0	14
Ln Real GDP	8.222613	1.110345	4.524124	10.45717
Observations	465			

Table 1: China data summary statistics

	mean	sd	min	max	count
Ln Coal contract quantity (tons)	2.8096	1.377317	-6.907755	8.282483	135315
Ln Real contract coal price per ton	3.55144	.3352458	-1.94591	6.861505	135315
Time trend	6.743687	4.946114	0	19	135315
Ln GDP	12.54432	.7256892	10.83782	14.87147	135315
Coal seam height (in.)	82.63363	22.40209	0	168	32290
Observations	135315				

Table 2: US data summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Ln Real coal price index_p,t	-0.0254	0.0795	-0.179**	0.0692	0.159*	0.162	0.0523	-0.183***	0.0740
	(0.1382)	(0.1303)	(0.0718)	(0.1407)	(0.0809)	(0.0993)	(0.0952)	(0.0657)	(0.1361)
Ln GDP_p,t	1.186***	1.420***	1.291***	1.269***	1.111***	1.112***	1.256***	1.234***	1.088***
	(0.2697)	(0.2967)	(0.3550)	(0.2548)	(0.2969)	(0.2896)	(0.4221)	(0.3050)	(0.2711)
Time trend_t	-0.0365	-0.0555**	-0.0605	0.0869*	-0.0224	-0.0225	-0.0212	-0.0323	0.215***
	(0.0230)	(0.0246)	(0.0388)	(0.0471)	(0.0267)	(0.0264)	(0.0396)	(0.0304)	(0.0684)
Ln Real coal price index_p,t × Time trend_t				-0.0301**					-0.0284*
				(0.0114)					(0.0147)
Ln Real coal price index_p,t-1					0.00883				
					(0.0740)				
Ln Real coal price index_p,t-2					-0.263***	-0.259***	-0.0722	-0.237***	0.0267
					(0.0624)	(0.0840)	(0.1247)	(0.0817)	(0.1831)
Ln Real coal price index_p,t-2 × Time trend_t									-0.0243
									(0.0171)
Constant	-5.211***	-7.492***	-5.194*	-6.252***	-4.381**	-4.388**	-5.892**	-3.926*	-5.069***
	(1.6401)	(1.9029)	(2.6460)	(1.6893)	(1.8495)	(1.8143)	(2.7218)	(2.2306)	(1.8172)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	379	255	124	379	320	320	196	124	320
R^2	0.975	0.981	0.994	0.977	0.979	0.979	0.985	0.994	0.982
Adjusted R^2	0.972	0.978	0.992	0.974	0.976	0.976	0.981	0.992	0.980

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Burke and Liao (2015) replication

Note: Table 3 presents OLS estimates where the dependent variable is Ln Coal consumption_p,t using the year-province panel of China coal consumption data. Standard errors are clustered at the province level in all specifications, as is done in Burke and Liao (2015). Columns (1), (4), (5), (6), and (9) use the full sample period (1998-2012); columns (2) and (7) use the early sample period (1998-2007); and columns (3) and (8) use the late sample period (2008-2012).

	(1) OLS, Full	(2) IV, Full	(3) OLS, Early	(4) IV, Early	(5) OLS, Late	(6) IV, Late	(7) OLS, Full	(8) IV, Full
Ln Real coal price per ton	-0.281**	-536.6	-0.190**	16.06***	-0.306	1.180	-0.280**	-8.458***
	(0.1254)	(4787.3744)	(0.0933)	(4.2734)	(0.3027)	(0.9754)	(0.1308)	(0.8835)
Ln GDP	-0.0148	222.4	0.765*	0.441	-1.312	-0.584	-0.0145	2.578***
	(0.4494)	(1995.2957)	(0.4610)	(0.7199)	(1.1596)	(0.7174)	(0.4443)	(0.4176)
Time trend	0.00115	-9.148	-0.0329***	-0.0114	0.0199	0.0166	0.00182	-1.514***
	(0.0090)	(81.8106)	(0.0109)	(0.0166)	(0.0205)	(0.0298)	(0.0690)	(0.1863)
Ln Real coal price per ton × Time trend							-0.000196	0.426***
							(0.0195)	(0.0558)
Constant	4.814	-910.9	-5.401	-60.01***	21.36	7.589	4.805	1.080
	(5.6320)	(8304.2359)	(5.7299)	(18.3735)	(14.9995)	(5.9649)	(5.4895)	(3.1056)
Power plant fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135315	32290	92481	16005	42834	16285	135315	32290
R^2	0.338	.	0.359	.	0.360	0.326	0.338	.
Adjusted R^2	0.336	.	0.357	.	0.357	0.318	0.336	.

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Linear time trend regression estimates

Note: Table 4 presents OLS and IV estimates of equation (5), where the first stage regression specifications of the IV estimates are given by equations (6a) and (6b), in which coal seam height is an instrument for the price of coal. The sample is long-term supply contracts for bituminous coal between coal mines and power plants. Columns (1), (2), (7), and (8) use the full sample period (2002-2021); columns (3) and (4) use an early sample period (2022-2010); and columns (5) and (6) use a late sample period (2011-2021). Standard errors are clustered at the power plant level for OLS estimates (in the spirit of Burke and Liao (2015)) and are heteroskedasticity robust for IV estimates.

Note: Table 5 presents OLS and IV estimates of equation (7), where the first stage regression specifications of the IV estimates are of the form of equations (8a) and (8b), in which coal seam height is an instrument for the price of coal. The sample is long-term supply contracts for bituminous coal between coal mines and power plants over the full sample period (2002-2021). The time trend variable is equal to the number of years since 2002, where 2002 is the base year. Standard errors are clustered at the power plant level for OLS estimates (in the spirit of Burke and Liao (2015)) and are heteroskedasticity robust for IV estimates.

	(1) OLS	(2) IV	(3) OLS	(4) IV
Ln Real coal price per ton	-0.294**	-55.77	-0.0946	-8.130***
	(0.1275)	(53.1698)	(0.1630)	(3.0357)
Ln GDP	0.0809	27.22	-0.0630	2.778***
	(0.5658)	(27.7473)	(0.5658)	(0.6463)
Time trend=0 × Ln Real coal price per ton			0	0
			(.)	(.)
Time trend=1 × Ln Real coal price per ton			-0.0819	-1.092
			(0.1051)	(1.3147)
Time trend=2 × Ln Real coal price per ton			-0.186*	0.607
			(0.1070)	(1.3654)
Time trend=3 × Ln Real coal price per ton			-0.0542	3.197**
			(0.1287)	(1.2517)
Time trend=4 × Ln Real coal price per ton			-0.0220	3.388***
			(0.1312)	(1.1849)
Time trend=5 × Ln Real coal price per ton			-0.288**	4.857***
			(0.1288)	(1.0323)
Time trend=6 × Ln Real coal price per ton			-0.281*	4.055***
			(0.1588)	(1.1657)
Time trend=7 × Ln Real coal price per ton			-0.344**	4.549***
			(0.1424)	(1.7546)
Time trend=8 × Ln Real coal price per ton			-0.236	5.272**
			(0.1496)	(2.4895)
Time trend=9 × Ln Real coal price per ton			-0.493***	6.390***
			(0.1803)	(1.5522)
Time trend=10 × Ln Real coal price per ton			-0.297*	6.856
			(0.1748)	(4.2932)
Time trend=11 × Ln Real coal price per ton			-0.276	9.642***
			(0.2062)	(1.9053)
Time trend=12 × Ln Real coal price per ton			-0.0800	14.29
			(0.2555)	(25.4793)
Time trend=13 × Ln Real coal price per ton			0.214	5.193
			(0.3600)	(4.6454)
Time trend=14 × Ln Real coal price per ton			0.252	3.716
			(0.3278)	(6.1906)
Time trend=15 × Ln Real coal price per ton			0.264	5.159**
			(0.2662)	(2.5156)
Time trend=16 × Ln Real coal price per ton			0.301	9.092***
			(0.3222)	(3.1009)
Time trend=17 × Ln Real coal price per ton			0.259	6.586***
			(0.4067)	(1.2124)
Time trend=18 × Ln Real coal price per ton			0.00631	2.197
			(0.4137)	(7.2145)
Time trend=19 × Ln Real coal price per ton			0.148	7.522
			(0.3888)	(11.9518)
Constant	3.756	-143.7	4.853	-2.101
	(7.1683)	(163.9811)	(7.1262)	(7.7173)
Power plant fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	135315	32290	135315	32290
R^2	0.341	.	0.343	.
Adjusted R^2	0.339	.	0.340	.

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Yearly time trend dummies regression estimates

	(1) OLS	(2) IV	(3) OLS	(4) IV
Ln Real coal price per ton	-0.266**	-42.07	-0.146	-5.808***
	(0.1236)	(28.2702)	(0.1344)	(0.5802)
Ln GDP	-0.0635	10.24	-0.114	1.072***
	(0.3643)	(7.6472)	(0.3654)	(0.2548)
Time trend=0 $\times$ Ln Real coal price per ton			0	0
			(.)	(.)
Time trend=1 $\times$ Ln Real coal price per ton			-0.232**	2.824***
			(0.1037)	(0.3818)
Time trend=2 $\times$ Ln Real coal price per ton			-0.0753	4.716***
			(0.2207)	(0.7344)
Time trend=3 $\times$ Ln Real coal price per ton			0.284	7.909***
			(0.3118)	(0.9640)
Constant	5.396	18.35	5.607	10.66***
	(4.6125)	(12.0960)	(4.5178)	(2.4404)
Power plant fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	135315	32290	135315	32290
R^2	0.339	.	0.340	.
Adjusted R^2	0.337	.	0.338	.

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: 5-year time trend dummies regression estimates

Note: Table 6 presents OLS and IV estimates of equation (7), where the first stage regression specifications of the IV estimates are of the form of equations (8a) and (8b), in which coal seam height is an instrument for the price of coal. The sample is long-term supply contracts for bituminous coal between coal mines and power plants over the full sample period (2002-2021). The time trend variable indicates five-year time periods beginning with the base period of 2002-2006 and continuing with 2007-2011, 2012-2016, and 2017-2021, respectively. Standard errors are clustered at the power plant level for OLS estimates (in the spirit of Burke and Liao (2015)) and are heteroskedasticity robust for IV estimates.